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Effects of using average annual daily traffic (AADT) with exogenous factors to predict daily traffic

Nedal T. Ratrout[a], Uneb Gazder[a], El-Sayed M. El-Alfy[b]

[a]*Department of Civil and Environmental Engineering, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia*
[b]*Department of Information and Computer Science, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia*

Abstract

Traffic demand can be highly correlated to the exogenous factors that exist outside the road system under study. Factors like day of week, presence of vacation or salary disbursement or economic parameters are readily available and may affect traffic flow between two countries. Collection of traffic data on a consistent basis is a cumbersome process in terms of time and resources. Considering these two factors in mind, this paper investigated the feasibility of using exogenous factors with Average Annual Daily Traffic (AADT). It was found that inclusion of AADT for traffic prediction is beneficial and further analysis will be done in the future with detailed traffic data.

Selection and Peer-review under responsibility of the Program Chairs.

Keywords: Traffic Forecasting; Exogenous Factors; Average Annual Daily Traffic

1. Introduction

Traffic demand is a function of exogenous factors as well as the growth or seasonal trend of the traffic itself. Exogenous factors indicate the parameters that exist outside the system of study like fuel prices. Traffic pattern changes in certain times of the week; this theory has been supported by Jong et al[1]. Goodwin[2] has proved in his research that changes in availability and service of one alternative also affects the travel demand on the other. Selection of exogenous factors to be included in the modeling also depends upon the location and importance of the road. In this regard, special consideration has to be given to border transport which requires that the political and economic conditions of both connected countries should be taken into account. Some of the studies like Petersen[3] and Rietveld[4] have used Gross Domestic Product (GDP) as the economic indicator in their models. But this parameter is only suitable for long-term predictions as its value does not change on a short-term basis.

* Corresponding author. Tel: +9-665-55842723; Fax: +9-661-38602879
Email address: nratrout@kfupm.edu.sa

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The aim of the research is to test the accuracy of predicting cross-border daily traffic with exogenous factors alone and using exogenous factors with aggregate traffic measure i.e. Average Annual Daily Traffic (AADT). AADT is the mean of daily traffic counts over a period of one year and is usually available, or can be estimated with reasonable accuracy, for most important roads in the country. It is often used in transportation planning and modeling as a surrogate measure of traffic[5,6].

King Fahd causeway, which connects Al-Khobar (Kingdom of Saudi Arabia; KSA) to Bahrain, has been selected as the study area for this research. The traffic which is modeled in this study is across borders of these two countries. Hence, the results of this study will be helpful in defining appropriate variable set for border traffic forecasting on daily to yearly basis. The methodology outlined in this research can also be used to gain similar objectives in other areas of traffic modeling.

Taking into account the work done previously in traffic forecasting, 10 exogenous factors have been included in the analysis. Time related parameters have been used for forecasting to extend the work of Jong et al[1] for daily traffic predictions. Airline travel was also used in the analysis because it is the alternate mode of travel for the causeway travelers and may affect its travel demand. Furthermore, stock market indices have been proposed to be used in the traffic forecasting models as the economic and political indicator.

The need for this study is that traffic data can be difficult to collect on a periodic basis and requires consumption of lot of time and resources. While exogenous factors like stock market indices are regularly monitored and collected so it is convenient to predict the traffic using only exogenous factors or with some aggregate traffic measure like AADT, which is commonly available for major corridors. A complete list and description of all the variables used in this study is given in section 2.

In this research, traffic forecasting models have been developed using artificial neural networks (ANNs). The accuracy of the ANNs has been improved by employing homogenous ensembles. Homogenous ensembles refer to the integration of multiple networks of the same type to give final results. Ensembles have been reported to give better performance than the individual models[7]. Section 3 provides detailed description of modeling process.

2. Dataset description and analysis

King Fahd causeway provides a land link for travelers between the KSA and the Kingdom of Bahrain. These two countries are very close to each other with a total length of the causeway about 25 kilometers. These countries also have strong social, political and economic ties which encourage their residents to travel more frequently between them. The data for this study was provided by the customs and ports directorate of the Kingdom of Bahrain. There are two modes of transport operating on the causeway: private vehicles and public transport. The average number of passengers using the causeway in both directions is above 48000 per day[8]. This causeway not only provides a connection for Saudi and Bahraini travelers but it is also the only road connecting Bahrain to other Gulf countries. Since there is no railway connection between Bahrain and KSA, the road and air transport are very important for travelers to and from Bahrain. All travelers from the Gulf countries go to Bahrain through this causeway passing KSA by land. Bahrain airport also acts as a hub for connecting flights to many countries of the world, so the people from the eastern region in KSA go to Bahrain through this causeway for catching flights to their destinations. This is one of the reasons that Saudi-Bahrain Transport Company (SABTCO) provides a frequent service from Bahrain Airport in Manama to their bus station in Dammam (KSA), with buses going to and from Bahrain on an hourly basis. Gulf airline, which is the national airline of Bahrain, also provides its bus service for the airline passengers from Bahrain airport to Dammam in KSA.

In this research, the dataset was available for traffic counts for the period from 1st January 2003 to 21st October 2013. For the analysis of this dataset 11 variables were used which were selected after the literature review of the previous studies; the summary of these variables is given in Table 1. Hajj dummy variable is included because these dates are announced as holidays in both countries. Similarly in summer vacations, educational institutes specially schools are closed. Moreover, dummy variable ‘A’ was also included because it is the period of the Islamic (lunar) month in which salary is disbursed to Saudi government employees. The purpose of including this variable was to test whether or not people would like to travel more for activities like shopping and recreation when they receive their salary. Considering the fact that the study area is across the borders of two countries, economic and political stability of the countries also becomes an important factor affecting travel demand. Therefore, stock market indices for both countries are proposed as indicators of political and economical stability of the region.

Saudi Stock Exchange, also known as Tadawul, is the only stock exchange in Saudi Arabia. It is supervised by a government organization called Capital Market Authority. It lists 156 publicly traded companies (as of September 2, 2012). Bahrain Bourse (BHB) was established as a shareholding company for the year 2010 to replace Bahrain Stock Exchange (BSE). Currently, there are 50 companies listed on the exchange. The BSE operates as an autonomous institution supervised by an independent board of directors. The descriptive statistics for the numerical variables in the dataset is given in Table 2.

Table 1: Summary of variables in dataset

Variable	Description
Variable A*	Dummy variable indicating period from 24th to 1st of each Islamic (lunar) month (0 or 1). It represents salary disbursement period for government employees
Hajj*	Dummy variable indicating period from 1st to 14th of 12th Islamic month (0 or 1)
Summer vacations	Dummy variables indicating months of June and July (0 or 1)
Name of weekday	Name of the weekday labeled by integers (1 to 7)
Daily stock index KSA	Daily index of Saudi stock market
Daily stock index Bahrain	Daily index of Bahraini stock market
Total traffic incoming	Total number of vehicles per day entering KSA through King Fahd causeway
Daily flights arriving	Total number of flights per day arriving at King Fahd international (KSA) airport from Bahrain international airport
Daily passengers arriving	Total number of passengers per day arriving at King Fahd international airport (KSA) from Bahrain international airport
Daily flights departing	Total number of flights per day departing from King Fahd international airport (KSA) for Bahrain international airport
Daily passengers departing	Total number of passengers per day departing from King Fahd international airport (KSA) for Bahrain international airport
Average annual daily traffic (AADT)	Daily traffic collected and averaged over the period of 365 days

*Shifting in Gregorian calendar each year

Table 2: Descriptive statistics of numerical variables in dataset (2003 – 2013)

Variable	Mean	Minimum	Maximum	Standard Deviation
Daily total traffic incoming (vpd)	8434	754	17100	2403.55
Daily stock index KSA	7656.79	2500.00	19600.00	3158.72
Daily stock index Bahrain	1704.38	1035.30	2902.68	526.16
Daily flights arriving	2	0	14	1.43
Daily passengers arriving	190	0	1402	141.20
Daily flights departing	2	0	16	1.52
Daily passengers departing	181	0	1968	147.77

3. Modeling Methodology

Approximately 33% of the data was used as the test set which was randomly selected at the start of the analysis and kept constant for all models to compare their results. The models were developed using artificial neural networks (ANNs) with increasing step sizes (prediction horizons denoted as 'K') and input data points (look-back periods denoted as 'P'). Multi-layer perceptron (MLP) is the type of ANN architecture used for this study. This architecture is used successfully in time-series forecasting studies[9]. In this model architecture, each neuron is fully connected to all neurons in the preceding layer. The outputs of each layer are weighted average of the input from previous neurons processed with pre-selected activation function. The number of neurons for specific layers and number of layers depend upon input and output variables and complexity of the problem[10].

Ensembles were created for different prediction horizons and each ensemble consisted of 7 component models. The component models were homogenous (MLPs) and used different ranges of time-series input data. For each prediction horizon, the range of look-back period was varied from 1 to 7 days. The range of look-back period was selected considering the fact that traffic peaks are repeated on weekly basis so this range would capture this trend. The ensembles were created for prediction horizons of 1 day, 1 week, 1 month, I quarter (3 months) and 1 year. Trends of input parameters were considered for selecting the prediction horizons. Factors like traffic counts, Islamic month dates for salary disbursement period, and stock market indices change their patterns on daily, weekly, monthly, quarterly and yearly basis. Hence this study also explored the limits to which these parameters are effective in forecasting border traffic. Ensembles were created by taking average of the outputs of the component models.

4. Traffic predictive models and ensembles

MLP ensembles were created using only exogenous factors and then with AADT and exogenous factors. The performance of the ensembles created using these variables was compared with each other to analyze the effectiveness of inclusion of AADT in the traffic flow predictions. Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were used as the measures of model performance. Table 3 presents the accuracies of models and ensembles without using traffic parameters while table 4 shows the accuracies after including AADT in the models.

Table 3: Predictive modeling by MLPs using exogenous factors only

P (Look-Back Period)	K (Prediction Horizon)									
	1 days		7 days		30 days		90 days		365 days	
	MAE	MAPE (%)	MAE	MAPE (%)	MAE	MAPE (%)	MAE	MAPE (%)	MAE	MAPE (%)
1 days	1479	20.76	1379	19.59	1382	19.55	1399	19.58	1219	17.29
2 days	1403	19.92	1405	19.58	1434	20.05	1305	18.47	1214	17.38
3 days	1391	19.66	1466	20.61	1463	20.14	1349	18.70	1324	18.59
4 days	1474	20.43	1460	20.45	1427	19.94	1425	20.09	1203	17.13
5 days	1512	20.26	1502	20.70	1429	20.07	1414	19.90	1321	18.63
6 days	1561	21.87	1444	20.13	1519	21.15	1401	19.61	1334	18.47
7 days	1409	19.77	1382	19.46	1366	19.23	1503	20.60	1288	18.41
Ensemble	1368	19.28	1342	18.93	1309	18.50	1309	18.49	1224	18.40

From Table 3, it can be observed that the accuracies of ensembles do not change when the value of prediction horizon is changed. The best models are achieved when the look-back period was between 2 to 7 days. So it can be concluded that more than one-day look-back period should be used for daily traffic predictions. Moreover, the ensemble accuracies do not change with respect to prediction horizon when exogenous factors are used with AADT for prediction, as observed from table 4. Accuracies also remain approximately constant with respect to look-back periods in this case. With both sets of variables, MLP ensembles perform better than their component models. Figure 1 represents a comparison of all MLP Ensembles created.

From Figure 1 and tables 3 and 4, it is evident that using AADT with exogenous factors for border-traffic forecasting improves accuracy of the ensembles, irrespective of the prediction horizon and look-back period. The improvement varies from 5.22% (P=6 days, K=1 days) to 0.11% (P=1 days, K=365days) for single MLP models, and from 3.32% (K=1 day) to 2.02% (K=365 days) for ensembles. Therefore it is concluded that using exogenous factors with a surrogate measure (AADT) is more efficient way to predict traffic.

Table 4: Predictive modeling by MLPs using exogenous factors and AADT

P (Look-Back Period)	K (Prediction Horizon)									
	1 days		7 days		30 days		90 days		365 days	
	MAE	MAPE (%)	MAE	MAPE (%)	MAE	MAPE (%)	MAE	MAPE (%)	MAE	MAPE (%)
1 days	1083	16.08	1113	16.45	1106	16.33	1144	16.82	1172	17.18
2 days	1070	15.97	1086	16.17	1101	16.25	1149	16.71	1168	17.14
3 days	1105	16.38	1105	16.39	1096	16.25	1168	17.06	1160	16.88
4 days	1101	16.30	1102	16.33	1143	16.85	1133	16.56	1171	16.96
5 days	1080	16.03	1133	16.73	1119	16.39	1199	17.42	1128	16.53
6 days	1124	16.65	1152	16.96	1129	16.65	1225	17.76	1183	17.04
7 days	1118	16.54	1132	16.91	1177	17.41	1156	16.84	1167	16.92
Ensemble	1072	15.96	1085	16.16	1079	16.20	1111	16.34	1114	16.38

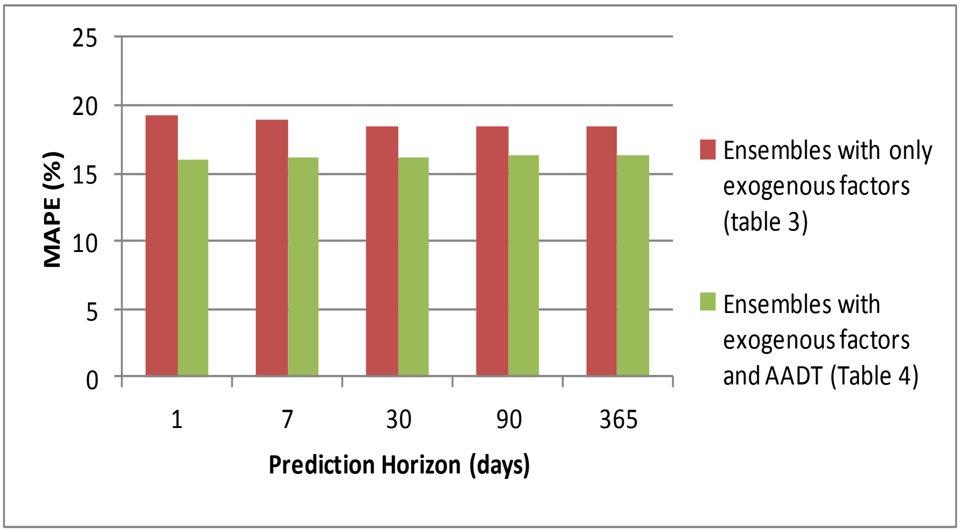

Fig. 1: Comparison of MAPEs for All MLP Ensembles

5. Discussion and Conclusions

The aim of this research was to test the effectiveness of exogenous factors with AADT in predicting cross-border daily traffic for prediction horizons of 1, 7, 30, 90 and 365 days ahead. The dataset used in this paper included King Fahd causeway causeway traffic, stock indices for KSA and Kingdom of Bahrain, flights and passengers traveling between Dammam (KSA) and Kingdom of Bahrain from 1st January 2003 to 21st October 2013. Apart from that, the name of the weekday and dummy variables for salary disbursement period and different types of vacations were also inserted in both datasets to be used as independent variables in predictive modeling of daily traffic. The variables were selected after review of other traffic forecasting studies as discussed in section 1.

For each prediction horizon, ensemble was developed consisting of 7 component models with increasing look-back period (P) from 1 to 7 days because the traffic pattern completes its cycle in a week. The ensembles were created by taking average of the homogenous component models with different look-back periods. The performance of MLP ensembles was better than the performance of single MLP models. All the ensembles were first created with exogenous factors only and then with exogenous factors and Average Annual Daily Traffic (AADT).

It was observed that accuracies of ensembles do not change with respect to prediction horizon whether exogenous factors are used with Average Annual Daily Traffic (AADT) or without it. However, single MLP models and ensembles perform better with AADT in all cases. The improvement in single MLP models as well as ensembles varies from 3-5% for daily predictions to 1-2% for yearly predictions.

Effectiveness of adding surrogate traffic measure for border traffic prediction inspires the need for adding more detailed traffic related parameters like daily traffic counts in the analysis. It will be undertaken in the future studies by the authors.

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